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Review

Bridging data-driven and model-based approaches for process fault diagnosis and health monitoring: A review of researches and future challenges

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ABSTRACT

Fault Diagnosis and Health Monitoring (FD-HM) for modern control systems have been an active area of research over the last few years. Model-based FD-HM computational approaches have been extensively developed to detect and locate faults by considering logical or mathematical description of the monitored process. However, because of parametric, measurement and model uncertainties, applicable approaches that endeavor to locate faults with great accuracy are likely to give false alarms. Recently, many research works have been conducted in order to tackle this issue by making a tradeoff between accuracy and robustness during the fault detection phase. Due to the recent advances in sensor technology, computational capabilities and dedicated software/hardware interfaces, data-driven FD-HM approaches have demonstrated that highly accurate fault detection is possible when the system monitoring data for nominal and degraded conditions are available. Therefore, it seems that more than one approach is usually required for developing a complete robust fault detection and diagnosis tool. In this paper, the features of different model-based and data-driven approaches are investigated separately as well as the existing works that attempted to integrate both of them. In this latter context, there have been only few works published in the literature and hence reviewing and discussing them is strongly motivated by providing a good reference for those interested in developing hybrid approaches for FD-HM.

1. Introduction

The increasing complexity of industrial systems and their related performance requirements have induced the need to develop new approaches for supervising them. Supervision includes monitoring tasks which aim to determine the system's operating state at each time. This issue can be divided into two distinct but complementary steps, namely:

- Detection which aims to identify the presence of an eventual fault in the system.
- Diagnosis which aims to determine the root causes of the detected fault. This task encompasses the fault isolation and identification steps which enable to characterize the type of fault, its size and its profile.

A system is considered in normal operating mode when it provides a set of desired functions i.e. the system is in fault free case. The occurrence of a fault in the system can generate a failure. The term *fault* is defined by Isermann (2006) as an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable condition while failure is a permanent interruption of a system's ability to perform a required function under specified operating conditions. In general, faults that occur in a physical system can be classified into three categories i.e. actuator faults (parameters changes), sensor faults (bias for example) and plant faults (leak in a tank for example).

These faults can lead to critical failures if they remain undetected. Therefore, there is a need to generate a set of fault indicators that should be significantly sensitive to these faults. In recent years, there has been an increasing interest in fault detection and diagnosis approaches in order to cope with such issue. Among these approaches, one can distinguish between data-driven approaches, model-based approaches and expert knowledge ones (Venkatasubramanian et al., 2003a; Venkatasubramanian et al., 2003b; Venkatasubramanian et al., 2003c).

Data-driven approaches (Ding et al., 2011; Joe Qin, 2003) consider the detection and the diagnosis as classification tasks. This classification can be either supervised or unsupervised. Among the

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most popular data-driven methods, one can cite Neural Networks (Zhang, 2000), Bayesian Networks (Nielsen, 2007; Pearl, 2014), Control Charts (Joekes & Barbosa, 2013; Montgomery, 2007), Principal Component Analysis (Yu, 2012), Partial Least Squares (Kruger, Wang, Chen, & Qin, 2001). These methods play an important role in modern monitoring systems especially for large-scale industry applications since they do not require a lot of computations and hence they are compatible with real-time constraints of dynamic complex systems. However, a preprocessing step is necessary to extract information before applying the data-driven approaches.

Model-based approaches (Ding, 2008; Isermann, 2005) are a good alternative when an access to a significant amount of data is not possible but an accurate analytical model is available. This model is generally build on the physics of the process to be monitored. For each time step, residuals, which depict the differences between the measured process variables and their estimates, are generated. Then, a decision rule is chosen to evaluate those residuals in order to detect a fault.

The generation of residuals can be accomplished by various methods: diagnostic observers (Luenberger, 1966; Yang, Ding, & Li, 2015), parity relations (Gertler, 1997; Zhong, Song, & Ding, 2015), Bond Graph (Ould-Bouamama, El Harabi, Abdelkrim, & Gayed, 2012; Paynter, 1961). A major advantage of these methods consists on their ability to provide a description of the dynamic behavior and a physical understanding of the system. However, in practice, it is very difficult to develop an accurate mathematical model that takes into account modeling errors and uncertainties, because some sources of uncertainty are not quantifiable. In order to address such issue, statistics and interval approaches have been developed. The former ones have represented the uncertainty with Gaussian stochastic variables while the latter supposed the uncertainties to be unknown but to stay within known and acceptable bounds.

Thereby, each approach has its own advantages and drawbacks. The development of hybrid approaches could improve the FDI performances and overcome the limitations of individual methods used separately. Besides, the state of the art encourages defining a common framework that enables the fusion of different approaches (Venkatasubramanian et al., 2003a; Ding, Zhang, Naik, Ding, & Huang, 2009).

Accordingly, in Sections 2 and 3, an overview of the methods from data-driven and model-based approaches respectively, is presented. Section 4 will highlight the benefits and limits of each approach through a comparative analysis and emphasize the interest of hybrid approaches. In Section 5, a review on the existing researches that aimed to bridge different approaches is carried out. Finally, the last section will discuss some perspectives about FD-HM with hybrid approaches and conclude the paper.

2. Data-driven approaches

Actual processes are increasingly automated, allowing the access to a sizeable amount of data. Therefore, it is natural to monitor the process using methods based on these data. For data-driven approaches, fault diagnosis can be considered as a two stages procedure that encompasses (1) fault detection and (2) classification.

The first stage aims at detecting whether the system behavior matches with the expected one while the second stage concerns the determination of the class (type) of fault. These two stages can be performed independently or combined to each other.

Within the data-driven approaches category, one can distinguish between supervised and unsupervised classification. In supervised classification, it is necessary to define the classes and label the training data i.e. provide the category label for each of them before the training procedure. This latter consists on feature extraction step which maps the high dimensional vectors to feature space in order to find certain projecting vectors with low-dimension. A common way to perform fault diagnosis is to employ statistical models which aim at classifying the data acquired from the monitored process into a normal operating condition class and a faulty (out of control) class or distinguishing between different fault classes. However, it is difficult to anticipate a priori all the possible ways in which faults can occur. In order to tackle this issue, different unsupervised approaches have been developed.

In the following, a review of supervised and unsupervised approaches, as well as discussions on their main advantages and drawbacks are carried out.

2.1. Supervised classification

Supervised classification uses historical data to construct a learning model, which is used for the fault detection and diagnosis of the new data. Among the most used methods, one can cite Bayesian Networks (Pearl, 2014) and Artificial Neural Networks (Zhang, 2000).

2.1.1. Bayesian Networks (BN)

A BN is a directed acyclic probabilistic graphical model introduced by Pearl (2014). BN has been successfully applied in various application domains including clinical decision support (Sesen, Nicholson, Banares-Alcantara, Kadir, & Brady, 2013), diagnostic diseases (Antal, Fannes, Timmerman, Moreau, & De Moor, 2003), genotype data analysis (Yan & Cercone, 2010), cancer metastasis modeling and prediction (Wang, Makond, & Wang, 2014), fault detection and diagnosis (Atoui, Verron, & Kobi, 2015b; Verron, Li, & Tiplica, 2010a; Verron, Tiplica, & Kobi, 2008; 2010b; Zhao, Wen, & Wang, 2015; Zhao, Xiao, & Wang, 2013). In particular, BN provides a powerful tool for knowledge representation and reasoning in presence of uncertainties (Correa, Bielza, & Pamies-Teixeira, 2009; Gaymard & Tiplica, 2014; Lu, Bai, & Zhang, 2009; Weidl, Madsen, & Israelson, 2005). Within this scope, BN has been used to represent Gaussian Mixture Model (GMM) which is a non-regular statistical model (Tao, Li, Zhu, & Li, 2012).This strategy enabled to deal with non-Gaussianity problem since the regular statistical models cannot be applied in such case. Another problem concerns modeling of temporal relationships between variables. It has been addressed by developing the Dynamic Bayesian Network (DBN) which combines static network with temporal information (Murphy, 2002).

The DBN has been applied to improve the quality of Internet service (Li, Cheng, Qiu, & Wu, 2009), to detect transient faults (Jha, Li, & Seshia, 2009), to identify the fault propagation pathways, and diagnose the root cause variables (Yu & Rashid, 2013). In Zhang and Dong (2014), the authors proposed a multi-time-slice DBN with a mixture of the Gaussian output to handle two principal issues: the missing data samples and the non-Gaussian process data.

Beyond its ability to reason with uncertain information, BN can use historical data and expert knowledge to complete the lack of data (Zhao et al., 2013). Moreover, multivariate control charts and other techniques as principal component analysis were modeled by a BN classifier which enabled to detect and isolate faults within the same framework (Atoui, Verron, & Kobi, 2015c; Verron et al., 2010a). This strategy had proved its robustness and good performance. However, the network structure is designed depending on the prior process knowledge and requires a large amount of training data. Furthermore, the prior probability determination and conditional probability table (CPT) computation are still challenging issues.

Thus, the effectiveness of BN depends on the various assumptions or conditions required for developing an accurate model. In